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A review on reliability assessment for wind power

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ABSTRACT

The application of wind energy in electric power systems is growing rapidly due to enhanced public concerns to adverse environmental impacts and escalation in energy costs associated with the use of conventional energy sources. Electric power from wind energy is quite different from that of conventional resources. The fundamental difference is that the wind power is intermittent and uncertain. Therefore, it affects the reliability of power system in a different manner from that of the conventional generators. This paper, from available literatures, presents the model of wind farms and the methods of wind speed parameters assessment. Two main categories of methods for evaluating the wind power reliability contribution, i.e., the analytical method and the Monte Carlo simulation method have been reviewed. This paper also summarizes factors affecting the reliability of wind power system, such as wake effect, correlation of output power for different windturbines, effect of windturbine parameters, penetration and environment. An example has been used to illustrate how these factors affect the reliability of wind power system. Finally, mainstream reliability indices for evaluating reliability are introduced. Among these reliability indices, some are recently developed, such as wind generation interrupted energy benefit (WGIEB), wind generation interruption cost benefit (WGICB), Equivalent Capacity Rate (ECR), load carrying capacity benefit ratio (LCCBR).

Contents

1. Introduction

Wind generation has become increasingly popular choice of technology for new capacity additions in power systems worldwide [1–4]. Several factors have contributed to this trend [5,6]. Environmental concerns and a constant increase in fossil fuel prices are central to these factors. Moreover, recent legislative moves for green-house gases limitation in the EU and similar laws currently under consideration in the US and other parts of the world make wind economically more competitive with other traditional sources of energy. There are also other factors, such as advances in the manufacturing and control technology, which also

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add to the attraction of wind as a 'green' source of energy. Wind has proved to be one of the most successful of all available source of renewable energy offering relatively high capacities, with generation costs that are becoming competitive with conventional energy source [7]. In China, enormous money and energy have been spent in the wind sources domain, the wind capacity has double approximately every year in the past 5 years. In 2007, the new wind capacity is 2449 MW, which ranks third in the world and just behind American and Spain. The accumulative total amount of wind capacity in 2007 is 6050 MW, which ranks fifth in the world. Chinese government expects that wind energy will share 10% of the primary energy supply in 2020. At present, the biggest wind electric field group in China is being built Jiuquan of Gansu province, and the accumulative total of wind electric field is 12,710 MW in 2015, and the whole invest is more than 15 billion dollars. The biggest wind electric field in China lies in Huilai of Guangdong province, which has generated electric power and the capacity of Huilai wind field, is 100 MW. The successful construction of Shanghai Donghai Bridge offshore wind farm, which will be finished in 2009, with installed 100 MW wind turbines, provides a series of advantages, such as master of evaluation of offshore wind energy, design, construction technology, etc. It is planned to establish offshore wind farm with 1000 MW in Zhejiang Province and Jiangsu Province, China [8,9].

However, wind energy systems suffer from a major drawback since the wind resource is intermittent, hence, is not available all of the time to make turbines run continuously [10–12]. Therefore, wind energy systems are considered as energy-replacement rather than capacity-replacement resources. The amount of energy that can be supplied by one or more sites depends on the wind resource available, the type of wind turbines used, and the nature of the load being supplied. For these reasons, it is fundamental to study the reliability of these generation systems and to assess the effects that they will have on the entire system and on its reliability [13,14].

Earlier studies, from available literatures, on the reliability of unconventional energy sources have dealt with the problem at a generation level. These studies attempt to include unconventional energy sources in reliability analysis of the generating system using the loss-of-load approach. Most of the reported work done on modeling wind power generation and on the application of such models to generation system adequacy evaluation is in the analytical domain [12,14–18]. Analytical methods usually proceed by creating separate generation models for the conventional unit and unconventional unit groups. The system reliability indices are obtained by combining the generation models of each group. A WTG unit is usually modeled as either a multi-state unit or an energy-limited unit. The chronological variability and interaction of wind speeds and thus the time-related wind power are ignored. Some works have been done recently on Monte Carlo simulation methods [13,19–23]. The random capacity output of a wind farm can be obtained using random simulation of wind speeds. The performance of a wind energy conversion system (WECS) can then be estimated by simulating the system over a sufficiently long time period. Dependencies in the system, such as wind speeds auto-correlation, can be easily included in this method.

This paper firstly presents the model of wind farms and the method for Weibull parameter estimation. Then the methods of power system reliability assessment are reviewed. Next, current main researches for wind power reliability evaluation are discussed, such as: wake effect, correlation of output power for different windturbines, effect of windturbine parameters, penetration and environment. Finally, it is been described about the reliability indices. There are some usual reliability indices, such as Loss of Load Expectation, Loss of Energy Expectation, Frequency of Loss of Load, Duration per interruption, Load Not Supplied per Interruption, Energy Not Supplied Interruption. There are also some new reliability indices to describe the character of wind power, such as wind generation interrupted energy benefit, wind generation interruption cost benefit, Equivalent Capacity Rate, load carrying capacity benefit ratio.

2. Wind farm model

2.1. Wind speed model

Energy from the wind is a form of solar energy. Winds are turbulent masses of air resulting from evening out the differences in atmospheric pressure created by the sun. Wind is, therefore, highly variable, site-specific and also terrain specific. It has instantaneous, minute-by-minute, hourly, diurnal and seasonal variations. Wind force varies with the square of wind speed whereas the power in the wind varies with the cube of the wind speed [18,24]. As an example, if the power (p) in the wind is known at a wind speed of 10 miles per hour (mph), and the wind speed increase to 11 mph, the power in the wind is as follows: $p \times \left(\frac{11}{10}\right)^3 = p \times 1.331$

This example shows that an increase in wind speed from 10 to 11 mph, just 1 mph, or 10%, cause a 33% increase in the wind power in the wind. A small increase in wind speed produces a large increase in power. Therefore, a very precise wind speed model is needed in reliability evaluation of a power system including wind energy conversion system.

Many studies have reported statistical tests on wind speeds using different distributions, such as Weibull, Rayleigh, r^2 and so on [19,25]. It is generally accepted that the Weibull distribution adequately represents the wind speed probability distribution for most sampling times. The wind velocity is treated as a random variable assumed to have a Weibull distribution given by the following probability density function [12]

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1}\exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{1}$$

where c is the scale factor and k is the shape factor. The equivalent cumulative probability function (wind speed duration curve) is

$$p(v \le v_x) = \int_0^{v_x} p(v)\,dv = 1 - \exp\left[-\left(\frac{v_x}{c}\right)^k\right] \tag{2}$$

Advantages of the Weibull distribution are that (1) it is a two-parameter distribution, depending only on c and k [hence more general than the Rayleigh distribution, which has $k = 2$, and easier to work with than the more general bi-variable normal distribution, which requires five parameters]. (2) In a wide number of cases the Weibull seems to give a reasonable fit to observed distributions. (3) With Weibull c and k values known at one height, a consistent methodology can be used to adjust these parameters to another desired height.

2.2. Method for Weibull parameter estimation

There are several methods which can be used to estimate the Weibull parameters c and k, depending on which wind statistics are available [18,24,26].

(1) Mean wind speed and standard deviation

If only the mean of wind speed $\bar{v}$ and the standard deviation σ are available (where $\sigma^2 = (v-\bar{v})^2$, and the angle brackets denote an average), then c and k are related to $\bar{v}$ and σ by

$$\begin{aligned} \bar{v} &= c\Gamma\left(1+\frac{1}{k}\right) \\ \left(\frac{\sigma}{\bar{v}}\right)^2 &= \frac{\Gamma(1+2/k)}{\Gamma^2(1+1/k)} - 1 \end{aligned} \tag{3}$$

where Γ is the usual gamma function and $\sigma/\bar{v}$ is the coefficient of variation. The c and k values can best be available by using the approximate relation of

$$k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086} \qquad c = \frac{\bar{v}/\Gamma}{(1+1/k)} \tag{4}$$

We can get the gamma function's value by consulting the gamma table.

(2) Least-squares

From the equivalent cumulative probability function of (2), we can get

$$\ln\{-\ln[1 - p(v \le v_x)]\} = k\ln v_x - k\ln c \tag{5}$$

If the observed wind speed are divided into n speed interval $0 - v_1,\ v_1 - v_2,\ \ldots\ v_{n-1} - v_n$, having corresponding frequencies of occurrence $f_1, f_2, \ldots, f_n$ and cumulative frequencies $p_1 = f_1$, $p_2 = f_1 + f_2, \ldots p_n = p_{n-1} + f_n$ then Eq. (5) transforms to the linear from $y = a + bx$ by the relations

$$x_i = \ln v_i \qquad y_i = \ln[-\ln(1 - p_i)] \qquad a = -k\ln c \qquad b = k \tag{6}$$

Due to the least-squares theory, we can get

$$a = \frac{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i y_i}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \tag{7}$$

$$b = \frac{-\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i + n\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n\sum_{i=1}^{n} x_i^2 \left(\sum_{i=1}^{n} x_i\right)^2} \tag{8}$$

Then the Weibull parameters c and k are related to the linear coefficients a and b by

$$c = \exp\left(-\frac{a}{b}\right) \qquad k = b \tag{9}$$

(3) Mean wind speed and fastest wind speed

Since data listing, such as local climatologically data give monthly mean wind speed but not the standard deviation, so the method one cannot be used unless some estimate of the standard deviation or equivalent parameter is obtained. But the monthly fastest wind speed is routinely published, so we can evaluate the Weibull parameters using the fastest wind speed. Supposing v_{max} is the fastest wind speed during the time of T.

Then the probability

$$p(v \ge v_{max}) = \exp\left[\left(-\frac{v_{max}}{c}\right)^k\right] = \frac{1}{T} \tag{10}$$

Inversion of (10) to solve to v_{max}, and division by Eq. (4) yields the relation

$$\frac{v_{max}}{\bar{v}} = \frac{(\ln T)^{1/k}}{\Gamma(1+1/k)} \tag{11}$$

According to the observed $\bar{v}$ and v_{max}, the appropriate k value can be solved iteratively. But to resolve the k using Eq. (11) directly is very complicated. Many observed data show that k is usual 1.0–2.6, so $\Gamma(1 + 1/k) = 0.9$. Then we can get the parameters of Weibull by following

$$k = \frac{\ln(\ln T)}{\ln(0.9 v_{max}/\bar{v})} \qquad c = \frac{\bar{v}}{\Gamma(1+1/k)} \tag{12}$$

(4) Maximum likelihood estimate

According to maximum likelihood estimate theory, likelihood function is built as

Following

$$L(k,c) = \prod_{i=1}^{n} f(v_i) = \prod_{i=1}^{n}\left(\frac{k}{c}\right)\left(\frac{v_i}{c}\right)^{k-1}\exp\left[-\left(\frac{v_i}{c}\right)^k\right] \tag{13}$$

where k and c's likelihood value can be solved by the following likelihood equations:

$$F_1 = \frac{\partial \ln L(k,c)}{\partial k} = 0 \qquad F_2 = \frac{\partial \ln L(k,c)}{\partial c} = 0 \tag{14}$$

Combine Eqs. (13) and (14) we can yield:

$$F_1 = \sum_{i=1}^{n}[1/k + \ln v_i - \ln c - (v_i/c)^k \ln(v_i/c)] = 0 \qquad F_2 = \sum_{i=1}^{n}[-k/c + (k/c)(v_i/c)^k] = 0 \tag{15}$$

Usually we use the Newton–Raphson method to solve this equation. According to Eq. (15), it derives the Newton–Raphson correct equation as following:

$$\begin{bmatrix} F_1(k,c) \\ F_2(k,c) \end{bmatrix} + \begin{bmatrix} \dfrac{\partial F_1(k,c)}{\partial k} & \dfrac{\partial F_1(k,c)}{\partial c} \\ \dfrac{\partial F_2(k,c)}{\partial k} & \dfrac{\partial F_2(k,c)}{\partial c} \end{bmatrix} \begin{bmatrix} \Delta k \\ \Delta c \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{16}$$

The simulation procedure used to solve the parameters of Weibull distribution includes the following steps:

Step 1: Taking the history data of wind speed $\{v_1, v_2, \ldots, v_n\}$.
Step 2: Choosing the appropriate initial values of $k^{(0)}$ and $c^{(0)}$.
Step 3: Taking $k^{(0)}$ and $c^{(0)}$ into Eq. (15) to calculate F_1 and F_2, then to calculate Jacobian matrix.
Step 4: According to Eq. (16), it can yield Δk and Δc.
Step 5: Constringency judging, $\max\{|F_1^{(m)}(k,c), F_2^{(m)}(k,c)|\} < \varepsilon_1$ or $\max\{|\Delta k^{(m)}, \Delta c^{(m)}|\} < \varepsilon_2$ in which ε_1 and ε_2 are maximum error allowed.
Step 6: If step 5 is not satisfied, then

$$k^{(m+1)} = k^m + \Delta k^{(m)} \qquad c^{(m+1)} = c^{(m)} + \Delta c^m$$

Then go to Step 3.

2.3. A wind turbine output characteristic

The electric output of the wind energy conversion systems (WECS) depends on the wind characteristics as well as on the aero-turbine performance and the efficiency of the electric generator. These factors must be combined to obtain a probabilistic profile of the WECS output. The wind unit starts delivering electrical output at a wind speed called the cut-in speed and reaches the rated electrical output at a wind speed called the rated speed. The electrical output is maintained constant at the rated value for further increases in wind speed by appropriate blade pitch control up to the cut-out or furling speed, beyond which the unit is shutdown for safety reasons. Between the cut-in and the rated speed, the relationship between the electrical output and the wind speed is non-linear due to the combined effects of aero-turbine and generator characteristics. Because of constant variations in the wind input, the output of a WECS lies between zero and the rated value for nearly half of the time or even longer for poor wind regime months [10,12,13,23,25]. A typical WECS electrical output curve is shown in Fig. 1.

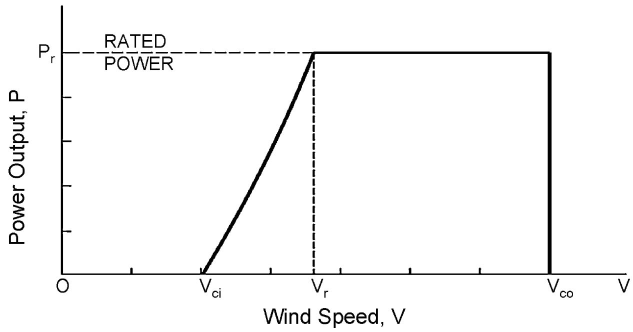

Fig. 1. A typical WECS output characteristic.

The parameters in Fig. 1 are: p_r = rated power output; v_{ci} = cut-in wind speed; v_r = rated wind speed; v_{co} = cut-out wind speed.

The WECS power output (p_{out}) can be calculated as:

$$p_{out} \begin{array}{ll} = 0 & 0 \le v \le v_{ci} \\ = (A + Bv + Cv^2)\, p_r & v_{ci} \le v \le v_r \\ = p_r & v_r \le v \le v_{co} \\ = 0 & v \ge v_{co} \end{array} \tag{17}$$

The constants A, B and C may be found as functions of v_{ci} and v_r using the following equations:

$$A = \frac{1}{v_{ci} - v_r}\left[v_{ci}(v_{ci} + v_r) - 4(v_{ci} \times v_r)\left(\frac{v_{ci} + v_r}{2v_r}\right)^3 \right]$$

$$B = \frac{1}{(v_{ci} - v_r)^2}\left[4(v_{ci} + v_r)\left(\frac{v_{ci} + v_r}{2v_r}\right)^3 - (3v_{ci} + v_r) \right]$$

$$C = \frac{1}{(v_{ci} - v_r)^2}\left[2 - 4\left(\frac{v_{ci} + v_r}{2v_r}\right)^3 \right]$$

3. Power system reliability assessment

The reliability associated with a power system, in a general sense, is a measure of the overall ability of the system to generate and supply electrical energy. Power system reliability can be further divided into the two distinct categories of system adequacy and system security [5]. Adequacy is an indicator of the existence of sufficient facilities within the system to satisfy future consumer load demand or system operational constants. Security is a measure of the ability of the system to respond to dynamic and transient disturbances arising within the system. Most probabilistic techniques available at the present time for power system reliability evaluation are in the domain of adequacy assessment. The ability to assess security is very limited [27]. The reason for this limitation is due to the complexity associated with modeling the dynamic and transient characteristics of a system. A complete power system can be categorized into the three segments, or functional zones, of generation, transmission and distribution. This division is an appropriate one as most utilities are either divided into these zones for one of these functions.

Hierarchical level I assessment, usually named as “generating capacity reliability evaluation”, mainly concerns assessing the installed generating capacity to satisfy the perceived system load and to perform necessary corrective maintenance at an acceptable risk level. Hierarchical level II assessment, usually termed “composite system reliability evaluation” or “bulk power system reliability evaluation”, considers generation and transmission systems. Hierarchical III assessment that is called “complete power system reliability evaluation”, considers all three functional zones, starting with generation and terminating at individual consumer load points.

Reliability calculation may be performed considering deterministic and probabilistic approaches [28]. Deterministic techniques are still used today for general studies, and in the past, were the practical application, when reliability became a relevant power system analysis issue, i.e., worst-case scenarios analysis. However, to apply deterministic techniques, the system had to be artificially constrained into a fixed set of values, which have no uncertainty or variability. The main drawback of deterministic techniques is that they do not assess the system’s stochastic behavior (i.e., forced outages of system components and uncertainty of customer demand). Probability methods were developed later, and can provide more meaningful information for design, resource planning, and resource allocation since they consider probability aspects of a system. Two main approaches can be considered for probability methods.

3.1. Analytical methods

The system is represented by mathematical models, and where direct analytical solutions evaluate the reliability indices from the models. The analytical solutions proposed by some authors use various interesting approaches [12,14–18]. The multi-state models [25,29,30] make use of wind turbine power output curve and wind speeds to generate partial power output states of wind turbine generators, which represent various energy levels indicating the correlation between fluctuating characteristics of wind speed and wind turbine power output. The number of these states is determined by characteristics of wind data and required accuracy. Load adjustment approach used by W.D. Marsh in his paper accounts for fluctuating energy by eliminating the power output from the utility load firstly, and then uses the adjusted load values not including wind energy to calculate the reliability indices. A method presented in reference [15] combines conventional and unconventional units into separate groups. One group contains the conventional units and the other group contains unconventional units. For each of these subsystems a generation system model is built using a recursive algorithm, employing full capacities of all units and the well known two and three state unit models. Conventional subsystem is calculated, and their generation system models modified to account for the effect of fluctuating energy. After this modification, all the generation system models are combined to find the loss of load expectation and the frequency of capacity deficiency for the hour under study. The combination of the generation system models of the different subsystems is performed using both a discrete state algorithm and the method of cumulates. The approach in references [14,16] also divides the conventional and unconventional units into different subsystems correlating output of subsystem of unconventional units with load, then using clustering procedure to identify system states, and finally combining subsystems in each state to obtain reliability indices of the whole system. In reference [17], the author use ant colony system (ACS) to scan and find out a set of most probable failure states which contribute considerably to system reliability indices. Rather than attempting to find a single optimal or near-optimal solution, ACS there is used as a search tool due to its nature of population-based random search.

In an analytical method, the capacity model is normally referred to as the capacity outage probability table, which provides the probability of occurrence for each possible outage capacity level. The assumption that the individual generating unit failures are independent events is always used.

3.2. Monte Carlo simulation

A Monte Carlo simulation approach is based on hourly random simulation to mimic the operation of a generation system, taking into account the fluctuating nature of wind speed, the random failures of generating units and recognized dependencies [13,19–23,31–34]. In fact, there are two basic techniques used when Monte Carlo methods are applied to power system reliability evaluation, these methods being known as the sequential and non-sequential techniques.

In current study, a non-sequential Monte Carlo method has been developed to evaluate the reliability indices of interest. This Monte Carlo simulation theoretically could incorporate any number of system parameters and states but it has been assumed, in our calculations that a generation unit was only able to reside in one of the following two states: fully available and unavailable. Moreover, in the established non-sequential simulation, only hourly uncorrelated states are considered as it is supposed that a generation unit outage state does not condition or influence its state during the next or previous hours of simulation. Finally, at the start of each hour, a uniformly distributed random number (u) on the interval [0,1] is drawn for each generation unit in order to decide its operation state, using the following procedure [21]:

- if $u \leq$ FOR, then the unit is decided to be unavailable;
- if $u >$ FOR, then the unit is available.

Sequential Monte Carlo simulation can be used to model all contingencies and operating characteristics inherent in the system [33]. A number of papers have been published [31–34] on the application of Monte Carlo simulation in the reliability evaluation. The major steps in using the sequential procedure with time varying loads for composite system reliability assessment are as follows [33]:

(1) The times to failure and times to repair of all components (generating units, transmission lines) for a yearly sequence are produced by sampling the appropriate probability distributions. In this procedure, the state residence times are assumed to be exponentially distributed. A random variate T with an underlying exponential distribution has a probability density function:

$$f_T(t) = \lambda e^{-\lambda t}$$

where λ is the mean value of the distribution. Using the inverse transform method, the random variate T is given by:

$$T = -\frac{\ln(1-u)}{\lambda}$$

where u is a uniformly distributed random number over the interval (0, 1). The availability of all system components are obtained for the simulated hour.

(2) The chronological hourly load model gives the load for the simulated hour at each bus.

(3) The simulated operation of the system is assessed. The network flow analysis is represented by a linearized power flow model. If it is a contingency state, a minimization model of load curtailment is used to reschedule generation outputs in order to maintain generation-demand balance and alleviate line overloads and, at the same time, to avoid load curtailment if possible or to minimize total load curtailment if unavoidable. The adequacy indices are accumulated.

(4) Steps 2 and 3 are performed for the yearly sequence of system states. The yearly adequacy indices are accumulated as $F(X_j)$, where X_j is the sequence of system states in year j. In order to evaluate the LOLP for instance, $F(X_j)$ is the sum of durations of all failure states divided by 8736 in the year j.

(5) If the coefficient of variation of the chosen index is greater than the tolerance level, steps 1–4 are repeated until convergence is achieved. The coefficient of variation β is calculated as:

$$\beta = \frac{\sqrt{V(F)/\mathrm{NS}}}{E(F)}$$

where $V(F)$ = variance of the test function, $E(F)$ = expected estimate of the test function and NS = number of simulated years.

(6) The adequacy indices are estimated as follows:

$$\text{expected value} = \frac{\sum_{j=1}^{\mathrm{NS}} F(X_j)}{\mathrm{NS}}$$

A number of papers have been published [13,19,22,23] on the application of sequential Monte Carlo simulation in the reliability of wind power system. In reference [13], the author uses the Sequential Monte Carlo techniques to generate artificial operating histories of the generating units. In reference [19], the evaluation of probability cost and reliability in the model is performed by using Monte-Carlo method for representing the uncertainty for wind speed and loads, forced outage rate of the units, the correlation of wind speed and load series, wind generation operational constraints. Reference [22] presents an application of Monte Carlo chronological simulation to evaluate the reserve requirements of generating systems, considering renewable energy sources. Reference [23] presents a time-sequential Monte Carlo simulation technique to evaluate the reliability cost/worth of a distribution system including WTGs.

4. Current main researches for wind power reliability evaluation

Power system reliability assessment with wind power has been studied for many years. Based on available literature, these researches are mainly concerning the relevant factors of the influence to wind power reliability and reliability indices.

4.1. Reliability indices

Reliability of power system is described mainly by reliability indices. There are some usual reliability indices, such as [2,5,13,27,35]:

- Loss of Load Expectation (LOLE), h/year;
- Loss of Energy Expectation (LOEE), MWh/year;
- Frequency of Loss of Load (FLOL), occurrence/year;
- Duration per interruption (D), h/occurrence;
- Load Not Supplied per Interruption (LNSI), MW/occurrence;
- Energy Not Supplied Interruption (ENSI), MWh/occurrence;

A WECS has a different impact on the load carrying capability of a generating system than does a conventional energy conversion system. This is due to the variation in wind speeds, the dependencies associated with the power output of each wind turbine generator in a wind farm, and the non-linear relationship between WTG power output and wind velocity. So in power system with wind farms, there are some special reliability indices to be used to describe the reliability of system [6,20,35,36].

(1) LCCBR (load carrying capacity benefit ratio)

The output of a WTG depends on the wind velocity which is intermittent. A 1 MW WTG cannot usually carry the same

amount of load as a 1 MW conventional generating unit. The following questions arise when considering wind energy as a potential power option.

(1) How much incremental peak load can a per unit injection of WECS capacity carry while maintaining the original risk criterion?
(2) What is the equivalence between conventional generation capacity and a per unit injection of WTG capacity?

The answers to these questions provide considerable information on the possible capacity credit that can be assigned to a WECS. The capacity factor can be used to provide an equivalent capacity measure [13].

$$CF = \frac{p_e}{p_r} \tag{18}$$

where p_e is the expected power output of a WECS, and p_r is the total rated power output. This factor indicates the potential wind energy production capacity at a wind site. It is, however, not related to the system capacity composition, the chronological load and wind profiles, and the accepted system risk level. Load carrying capacity benefit ratio is defined as the ratio of the incremental peak load carrying capacity due to addition of generating capacity over the amount of capacity added. Fig. 2 illustrates the relationship between a risk index and the annual peak load before and after adding WTG units. In Fig. 2, R_c is the criterion reliability, $PLCC_{org}$ is the peak load that the original generating system can carry at risk level R_c. $PLCC_{new}$ is the peak load that the expanded generating system (with the additional of WTG's) can carry at the same risk level.

The incremental load carrying capacity benefit from the WECS addition is

$$IPLCC_w = PLCC_{new} - PLCC_{orig} \tag{19}$$

The $IPLCC_w$ as a percentage of the added WTG generating capacity is designated as the WECS Load Carrying Capacity Benefit Ratio and is given by

$$LCCBR = \frac{IPLCC_w}{P_r} = \frac{PLCC_{new} - PLCC_{orig}}{P_r} \tag{20}$$

The LCCBR indicates the per unit incremental peak load that the system can carry due to the WECS addition while maintaining the criterion reliability. This index is a function of the system and the equipment parameters used in the analysis.

(2) ECR (Equivalent Capacity Rate)

If the additional wind capacity is replaced by conventional units with the same capacity p_r MW, the corresponding incremental peak load carrying capacity can be designated as $IPLCC_c$. The Equivalent Capacity Rate (ECR) is defined as the ratio of the incremental peak load carrying capacity of a WECS addition and the incremental addition [20].

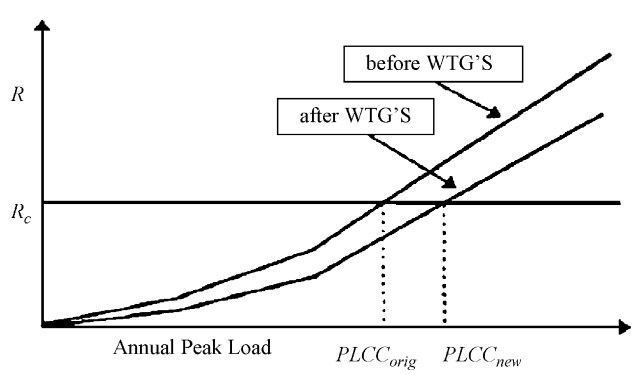

Fig. 2. variation of reliability indices with annual peak load.

$$ECR = \frac{IPLCC_w}{IPLCC_c} \tag{21}$$

The ECR provides a risk-based equivalence between conventional power and the WTG power. If the assessed ECR is 0.2, then 1 unit of WTG is equivalent to 0.2 units of conventional capacity, or 1 unit of conventional capacity is equivalent to 5 units of WTG, in that they provide the same incremental peak load carrying capacity.

(3) Energy and cost benefit indices

The reliability worth of adding wind generation as an alternative supply can be represented by an index designated as the wind generation interrupted energy benefit [23,36].

$$WGIEB = \frac{EENS_{bw} - EENS_{aw}}{\text{Incremental WTG capacity}} \tag{22}$$

where $EENS_{aw}$ and $EENS_{bw}$ represent the energy not supplied after and before adding WTG units respectively. The reliability worth of adding wind generation as an alternative supply can also be represented by an index designated as the wind generation interruption cost benefit (WGICB).

$$WGICB = \frac{ECOST_{bw} - ECOST_{aw}}{\text{Incremental WTG capacity}} \tag{23}$$

where $ECOST_{aw}$ and $ECOST_{bw}$ are the expected interruption cost after and before adding WTG units to the system respectively.

4.2. Relevant factors of influence

From the available literature, we can learn that the following aspects for wind generation's realistic reliability assessment are clearly important:

(1) Wake effect.
(2) Correlation of output power for different windturbines.
(3) Effect of windturbine parameters.
(4) Effect of penetration.
(5) Environment.

Each of these aspects will be individually analyzed in the following sections.

(1) Wake effect

Wind generators generate electricity by tapping into the energy in the wind. Consequently, the air mass leaving the turbine must have lower energy content and by implication lower speed than the air arriving in front of the turbine. In other words, the turbine positioned upstream in the wind direction influences the wind speed at turbine locations on its downwind (lee) side. This shadowing effect from upstream turbines on other turbines further downstream is referred to as the wake effect [37]. The implication of the wake effect is that the speed of free wind can be used for computation of mechanical power only for those turbines facing the wind up front. For all other turbines the applicable speed needs to be determined, possibly by taking the cumulative effect of multiple upstream turbines into consideration.

(2) Correlation of output power for different windturbines

The correlation between different wind speed conditions and therefore windturbine output powers must be considered if the assessment includes wind farms from different locations. The closer the windfarms, the more relevant

correlation has to be considered [25,38,39]. The problem arises with the simulation of the wind speeds in several wind farms when they are simultaneously calculated, because a correlation between them may exist. One way of solving the simulation of multivariate distributions with given correlation is explained by Feijoo et al. [38]. According to this method, given a vector of independent variables $z = (z_1, z_2, \ldots, z_n)^T$, with mean $\mu_z = (\mu_{z_1}, \mu_{z_2}, \ldots, \mu_{z_n})^T$, and covariance matrix:

$$\Omega_z = \begin{pmatrix} \sigma_{z11}^2 & \sigma_{z12}^2 & \cdots & \sigma_{z1n}^2 \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \sigma_{zn1}^2 & \sigma_{zn2}^2 & \cdots & \sigma_{znn}^2 \end{pmatrix}$$

A new vector $y = (y_1, y_2, \ldots, y_n)^T$, with mean $\mu_y = (\mu_{y_1}, \mu_{y_2}, \ldots, \mu_{y_n})^T$. Covariance matrix

$$\Omega_z = \begin{pmatrix} \sigma_{y11}^2 & \sigma_{y12}^2 & \cdots & \sigma_{y1n}^2 \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \sigma_{yn1}^2 & \sigma_{yn2}^2 & \cdots & \sigma_{ynn}^2 \end{pmatrix}$$ can be obtained through the

procedures:

(1) $y = Lz + \mu_y$, where L is a lower triangular
(2) $\Omega_y = LL^T$
(3) $E(y) = LE(z) + \mu_y$
(4) $\Omega_y = L\Omega_z L^T$, when $\mu_z = (0, 0, \ldots, 0)^T$ and

$$\Omega_z = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}, \quad \Omega_y = LL^T$$

The simulation of multiple wind farms is followed by the procedure:

(1) Generate the wind speeds without correlation through the Monte Carlo simulation, according to the specific parameter of different wind farms.

$$z = (z_1, z_2, \ldots, z_n)^T$$

(2) Subtract the mean values of each wind site from the wind speed gotten in first step, and divide the results by the standard deviation.

$$z' = \frac{z - \mu_z}{\sigma_z}, \quad \mu_{z'} = (0, 0, \ldots, 0)^T \text{ and } \Omega_{z'} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

(3) Obtain the transmission matrix L, while the wind covariance matrix $\Omega_y = LL^T$
(4) $y = Lz' + \mu_y$ and then we can yield $y = (y_1, y_2, \ldots, y_n)^T$
(3) Effect of wind turbine parameters

A small reliability test system designed as the RTS [40] is utilized as an example to illustrate the effect of windturbine design parameters on generation capacity adequacy [6,27]. The RTS has 11 conventional generating units, ranging in size from 5 to 40 MW, with a total installed capacity of 240 MW. The chronological load profile consists of 8736 load point and annual peak load is 185 MW. A WECS with a total capacity of 22.5 MW is incorporated in the RTS.

Table 1
RTS reliability indices with and without 100 WTG units.

Case	LOLE (h/year)	LOEE (MWh/year)	FLOL (occurrence/year)	*D* (h/occurrence)
Original system	1.1282	10.3109	0.2194	5.1414
With 100 WTG	0.7895	7.3572	0.1910	4.1330

Table 2
Effect of cut-in wind speed on the basic indices.

Cut-in speed (km/h)	LOLE (h/year)	LOEF (MWh/year)	FLOL (occurrence/year)	*D* (h/occurrence)
8	0.6921	6.3993	0.1728	4.0041
10	0.7459	7.0044	0.1873	4.0601
12	0.7859	7.3572	0.1910	4.1330
14	0.8383	7.8505	0.2010	4.1712
16	0.8911	8.3312	0.2070	4.3049
18	0.9290	8.3522	0.2131	4.3205

Table 3
Effect of cut-in wind speed on the LCCBR.

Cut-in speed (km/h)	IPLCC (MW)	LCCBR (%)
8	5.2	23.11
10	4.6	20.44
12	4.2	18.67
14	3.3	14.67
16	2.7	12.00
18	2.2	9.78

The wind speed mean and standard deviation at this sit are 14.63 and 9.75 km/h respectively. The actual hourly wind speed for 3 years and the hourly mean and standard deviation of wind speeds from a 37-year database for the site were obtained. The residence time distributions of all units were assumed to be exponential and a stopping criterion of $\varepsilon_{LOLE} = 0.05$ were used to control the simulation length. The following data and graphs come from references [6,27]. We use them to clearly show the effect of windturbine design parameters on generation capacity adequacy. The mean of the reliability indices with and without the WECS for the base case are given in Table 1.

(1) Effect of cut-in wind speed

The cut-in wind speed is assumed to range from 8 to 18 km/h while other parameters remain the same as those in the base case. Tables 2 and 3 respectively present the effects of different cut-in wind speed on the basic reliability indices and the Load Carrying Capacity Benefit Ratio of the RTS. The relationship between cut-in wind speed and LCCBR is illustrated graphically in Fig. 3.

It can be seen from Table 3 and Fig. 3 that the cut-in wind speed has a significant effect on the capacity adequacy and thus on the load carrying capacity benefit.

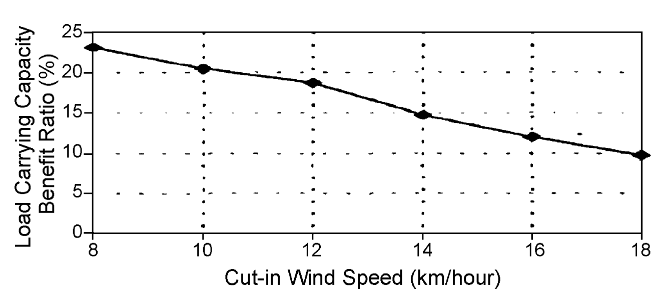

Fig. 3. LCCBR versus cut-in wind speed.

Table 4
Effect of rated wind speed on the basic indices.

Rated speed (km/h)	LOLE (h/year)	LOEE (MWh/year)	FLOL (occurrence/year)	*D* (h/occurrence)
32	0.7466	6.9406	0.1900	3.9304
34	0.7635	7.1250	0.1907	4.0028
36	0 7797	7.2492	0.1932	4.0555
38	0.7895	7.3572	0.1910	4.1330
40	0.8089	7.5578	0.1936	4.1772
42	0.8197	7.7092	0.1941	4 2221

Table 5
Effect of rated wind speed on the LCCBR.

Rated speed (km/h)	IPLCC (MW)	LCCBR (%)
32	4.6	20.44
34	4.4	19.56
36	4.3	19.11
38	4.2	18.67
40	4.1	18.22
42	4.0	17.78

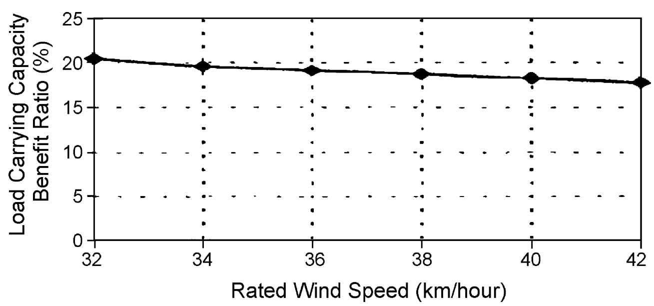

Fig. 4. LCCBR versus rated wind speed.

Table 6
Effect of cut-out wind speed on the basic indices.

Cut-out speed (km/h)	LOLF (h/year)	LOEE (MWh/year)	FLOL (occurrence/year)	*D* (h/occurrence)
40	0.7932	7.4150	0.1941	4.0860
50	0.7903	7.3589	0.1916	4.1237
60–90	0.7895	7.3572	0.1910	4.1330

(2) Effect of rated wind speed

Six different rated wind speeds ranging from 32 to 42 km/h were utilized to investigate the effect of rated wind speed on the adequacy and load carrying capacity benefit. The results are present in Tables 4 and 5 and Fig. 4.

It can be seen from Tables 4 and 5 and Fig. 4 that the rated wind speed has a relatively small effect on the capacity adequacy and load carrying capacity. This effect is less than that of the cut-in wind speed.

(3) Effect of cut-out wind speed

Tables 6 and 7 present the relationship between the cut-out wind speeds, the basic reliability indices and the Load Carrying Capacity Benefit Ratio. It can be seen that the cut-out wind speed has virtually no effect on the capacity adequacy and LCCBR. The cut-out wind speed is a safety parameter and is usually quite large. Only for relatively few time periods will the actual wind speed at a particular wind site be larger than the cut-out speed.

Table 7
Effect of cut-out wind speed on the LCCBR.

Cut-out speed (km/h)	IPLCC (MW)	LCCBR
40	4.2	18.22
50	4.1	18.22
60–90	4.2	18.67

Table 8
Effect of hub height on the basic indices.

Hub height (m)	LOLE (h/year)	LOEE (MWh/year)	FLOL (occurrence/year)	*D* (h/occurrence)
10	0.7895	7.3572	0.1910	4.1330
14	0.7894	7.3009	0.1892	4.1724
18	0.7600	7.1737	0.1864	4.0781
22	0.7407	7.0893	0.1797	4.1219
26	0.7154	6.5107	0.1776	4.0280
30	0.7095	6.4356	0.1783	3.9786

Table 9
Effect of rated wind speed on the LCCBR and ECR.

Hub height (m)	IPLCC (MW)	LCCBR (%)	ECR
10	4.2	18.67	0.1700
14	4.3	19.11	0.1741
18	4.4	19.56	0.1781
22	4.0	20.44	0.1862
26	4.7	20.89	0.1903
30	4.7	20.89	0.1903

(4) Effect of hub height

Wind speed increases with hub height. The effect of projected height on the generation adequacy and capacity benefit is presented in Table 8. The reference height is assumed to be 10 m. It can be seen from the Table that the hub height has a relatively small effect on the generation capacity adequacy and the incremental capacity benefit. This effect is less than that of cut-in wind speed. The Load Carrying Capacity Benefit Ratio increases approximately from 18% to 20% as the hub height increase from 10 to 30 m. These values are based on the approximate formula relating wind velocity to hub-height.

(5) Effect of penetration

The term "penetration" is defined as the percentage of wind capacity in the total combined conventional and unconventional system capacity. It has a significant effect on generation adequacy. Many researches have been done about how penetration affects the reliability of power system [10,27,35,41,42]. In these researches, most of them are studies that which level of penetration is the best and the difference between the WECS and its equivalent conventional capacity. In reference [35], wind farm, equivalent energy conventional unit and equivalent capacity conventional unit are compared to study the difference of their penetration. At wind penetration levels of less than 5%, the reliability impact of the wind farm is comparable to the impact of an energy equivalent conventional unit. However, for penetration level greater than 5%, the wind

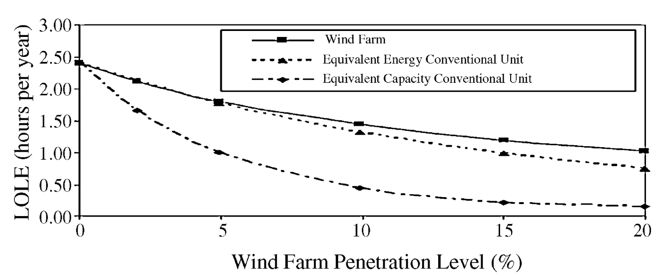

Fig. 5. Yearly LOLE of wind generation, equivalent energy and capacity conventional generation.

farm is less efficient in reducing the LOLE than the capacity equivalent conventional unit (Table 9).

(6) Environment

Little data are available for maintenance and failure/repair rates for WTs due to their relatively new development. Data for onshore WF failures and maintenance in Germany, Denmark, and USA are collected in G.J.W. van Bussel and M.B. Zaarijer's paper and DOWEC Team's paper. Figures for availability are shown, which consider different WT concepts, future evolution, and necessary offshore installation improvements. A similar approach is presented in A. Sannino's paper. All three papers consider the following as relevant aspects for installations [5] (Fig. 5).

- MTTR (mean-time-to-failure) can greatly increase during bad weather (e.g., winter), because the time to reach and repair a failed component is related to the bad-weather window's length.
- Failure rate may increase due to marine conditions, or to an installation site which is closeness to a sailing route.
- Component quality should be improved in order to compensate the two above-mentioned problems.

5. Conclusion and prospect

It can be predicted that the utilization of wind energy will rapidly increase due to more and more energy pressure in future. Consequently, it has a need to seriously consider the reliability of supply that can be obtained in addition to the associated cost benefits that can be achieved. Many solutions have been presented to assess WF reliability, but all lack the inclusion of all relevant aspects.

Based on available literatures, this paper firstly describes the model of wind farms and the method for Weilbull parameter estimation. Then the methods of power system reliability assessment are reviewed. Next, currently main researches for wind power reliability evaluation are discussed, such as wake effect, correlation of output power for different windturbine, effect of windturbine parameters, penetration and environment. Finally, it is been described about the reliability indices. There are some usual reliability indices, such as Loss of Load Expectation, Loss of Energy Expectation, Frequency of Loss of Load, Duration per interruption, Load Not Supplied per Interruption, Energy Not Supplied Interruption. There are also some new reliability indices to describe the character of wind power, such as wind generation interrupted energy benefit, wind generation interruption cost benefit, Equivalent Capacity Rate, load carrying capacity benefit ratio.

So far, in all the researches of wind power system reliability assessments, we only consider how many occurrences and how much time of outage to evaluate the reliability of power system. But, with more and more precise devices to be used, transient power energy quality must be considered, such as system average variation of frequency index and short voltage outage.

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